Chinese Wheat Price Analysis—*with Application of Cointegration and Granger Causality Test*

A Thesis

Presented to

The Academic Faculty

by

Yuanxiang. Guo

In Partial Fulfillment

of the Requirement for the Degree

Master of Science in the

School of Economics

Georgia Institute of Technology

December 2013

Chinese Wheat Price Analysis—*with Application of Cointegration and Granger Causality Test*

Approved by:

Dr.Tibor. Besedes Advisor
School of Economics
Georgia Institute of Technology

Dr. Shatakshee. Dhongde
School of Economics
Georgia Institute of Technology

Dr. Juan. Moreno—Cruz
School of Economics
Georgia Institute of Technology

Date Approved: November , 2013

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

SUMMARY

Traditional demonstration of price fluctuation in the wheat market, by the theory of supply and demand is not comprehensive enough. With limited understanding of macroeconomic effects on the wheat market, accurate prediction of wheat price is impossible. Given the Chinese self—sustainable food policy, grain imports is a sensitive topic which may incur fierce argument. In this paper, however, I emphasize effect of exchange rate on nominal wheat price. By application of the cointegration theory, CPI shows slight negative correlation with nominal wheat price, yet GDP and population move in the same direction as the wheat price. The cointegration study of exchange rate implies, with appreciating Chinese RMB, domestic buyers incline to purchase wheat from the cheaper foreign market. According to the Granger causality test, the whole package of variables suggests significant causal relation with the wheat price.

CHAPTER 1

INTRODUCTION

With rapid trend of globalization, Chinese domestic wheat consumption is heavily dependent on import. Dichotomized explanation of supply and demand is oversimplified or even leading to misleading results. The ultimate purpose of this paper is to use cointegration and Granger Causality test to unravel impacts from basic macroeconomics elements on yearly nominal wheat price. Although, plethora of articles pertains to macroeconomics elements on Chinese wheat price are published. Exchange rate, which still remains in area of shadowy penumbra, is seldom shed light on. In this paper, I will demonstrate how wheat price move in tandem with fluctuating exchange rate. All data is obtained from database of National Bureau of Statistics of China and Chinese National Department of Agriculture and Fishery. I processed all the data by application of Eview6.

Great famines are mostly witnessed in dictatorship countries, due to a lack of domestic consultation and absolute deference to totalitarianism. Less developed countries are usually more susceptible to price undulation in food market than developed countries, given inefficient social insurance system and less organized government structure. According to World Bank report, 60% of total population in Zambia and Tanzania still suffer from famine and malnutrition(The Food Watch ,2011).

China is the most populated country in the world. According to Nation Master database in 2012, China consumes 104,500 thousand metric tons of wheat, exceeding the Indian consumption by 40%, dominating other countries(Agriculture Stata ,2012). The World Bank monthly agricultural reports indicate, from November 2011 until April 2012 there is salient trend of bulging prices in market for rice, maize, and wheat; price index of wheat has escalated by more than 40%(Food Price Watch, 2012). The January 2011 Report suggests, global wheat price almost doubled from the low point of 2010 to its height in January, 2011 (Food Price Watch,2011). However, elevation of wheat price during the year of 2010, is nowhere near the catastrophic food crisis of 2008. Viveros (2012) emphasizes that severe drought in Sudan and Australia substantially increased the global wheat price.

In study of Chinese wheat price, conventional theory of dichotomized analysis about demand and supply, could lead to weak or even fallacious results. Kuijs (2011) asserts that around 75%~80% of Chinese wheat consumption is imported from the United States and Canada. Considering vast volume of foreign exchange reserves, Chinese government is no parsimonious in importing wheat from the United States, Canada, and Australia. Rising wheat price exerts additional pressure on less developed countries which survive on imported wheat. Viveros (2012) argues, in the 2008 food crisis, a large number of countries are affected by increasing wheat prices. Wheat prices perturbation occurred in Ethiopia and South Africa, and severe drought caused rising rice price in Tanzania and Uganda. Massive reduction in the rice production was witnessed, due to inundation (Viveros, 2012).

Before the inception of 1978 Economics Reform, China was an agriculturally self—sustainable country, grain consumption was all from domestic production. However, with the Open Door Policy, the Chinese government preferred to import cheaper wheat from foreign markets rather than producing all grains domestically. Wheat shortages sporadically occurred in the last half of the 20th century. In instead of distributing barley and sorghum in years of insufficient wheat production, as the Chinese government usually did in the 1970s and 1980s; in the past few years, with rapidly bulging economy, the Chinese government inclined to purchase high quality wheat from the United States and Canada. Traditional methodology of supply and demand in a closed economy is no more plausible to give an accurate result. Like other commodities, wheat price increases with inflating CPI. The GDP, as an indicator for a country's purchasing power is considered as an important determinant. Constant population growth also generates upward pressure for wheat price. Exchange rate, which is seldom mentioned in studies of closed economy, will be paid particular attention in this paper.

Zhang and Wang (2011) argue, per capita GDP in China has reached \$3266.48 which is the threshold for national structural change in grain consumption. With a higher standard of living, as residents emphasizes more on commodity variety, wheat consumption will gradually weaken in the long—run. They argue that although unexpected large shocks in the demand for wheat are rarely witnessed, since wheat does not have much industrial value as maize, population growth and changes in the diet structure also influences demand side of wheat market.

Wheat accounts for more than 45% of daily grain consumption among most Chinese families (Lin, 2009). In sub-frigid zone, wheat outperforms rice in withstanding hash cold winters and results in generally more plentiful harvests. Rice prospers in the warm region south of the Chung River, while harsh winters in the North can easily destroy a crop. On the contrary, wheat can withstand extremely low temperature often found in Manchuria and extraordinarily anoxic conditions such as in Tibet (Norbu, 2011). Apart from the beneficial genetic characters, wheat does not have conspicuous fluctuation in supply due to seasonality (Lin, 2009). Since the reservation cost of wheat inventory is lower than other crops, a steady supply of wheat across the whole year is plausible.

CHAPTER 2

LITERATURE REVIEW

A large amount of articles are published focusing on oscillation of prices in agricultural markets. Ezekiel (1938), first perceived the price in grain markets as a dynamic system, due to suppliers' expectations. The diagram of the dynamic convergence of price resembles patterns of a cobweb; thus diagrammatically, the model is titled "Cobweb Model". To some extent, it oversimplifies the exogenous variables subject to shocks from the external environment. Irrational expectation is the only element which causes a deficiency or surplus of supply.

Gouel (2010) provides a comprehensive summary of literatures on agriculture prices. Buchanan (1939) argued there is an intrinsic flaw in the original Cobweb model, in the case of a divergent price, producers may suffer long-term pecuniary losses. Hotoon (1950) and Akerman (1957) demonstrate in short-term, the supply is not so inelastic as Ezekiel presented in the Cobweb model; the stock could alleviate the inelaticity. In other words, creating a long-run volatility is seldom seen in reality. Through the late 1930s until the 1960s, although there are a large amount of articles published, studies of agriculture economics generally remain stagnant until Muth (1969) introduces revolutionary idea of rational expectation into this field. Muth (1969) criticizes traditional Cobweb model overly emphasizing the importance of irrational expectation, inventory can clear the market in either case of surplus or deficiency of supply, and always keeping market equilibrium. His contribution is to solve the first order serial-correlation in inventory speculation. By assuming the disturbance follows the pattern of White noise, and eventually give the formula of price in form of $p_t^e = {}^{\beta}/_{\theta} \sum_{t=1}^{n} \left({}^{\theta}/_{(\theta+\beta)}\right)^j p_{t-j}$.

In the 1980s, economists are dissatisfied with Muth's demonstration. They ignored the over-emphasis on erroneous expectation, and coming back to the original Cobweb model. Artstein (1984) and Jensen (1983) uphold the plausibility of the traditional cobweb model. However, they criticize monotonic linear equation differs from empirical data. By analyzing an overwhelming amount of raw data, Artstein (1984) and Jensen (1983) modify the original linear supply function, instead they write the equation in the form of q_t^s= arctan λ^{pt}.

Brock and Hommes (1997) enhance the rudimentary Cobweb model by introducing the novel concept of “a heterogeneous Agent”, which means multiple agents can produce idiosyncratic products and react differently in the face of exogenous shocks. Gouel summarizes debates among two major groups of economists which represent theory of rational expectation and erroneous market evaluation.

Notwithstanding, research on agriculture price index pertains to macroeconomic elements presents no innovations until Enger (1987) and Johnasen (1991) contrive cointegraton method to articulate the long run trend without inference of spurious correlation. Cointegration is commonly applied in the study of long-run grain prices. Dombusch (1976) pays attention to excessive money supply which induces direct upward pressure on the price of agricultural commodities. Orden (1986) demonstrates that the exchange rate is a vital factor to exert impacts on the US wheat price, while Chambers and Just (1987) endogenize the exchange rate as an independent variable in the model. Using the modern methodology of cointegration, Denbaly and Torgerson (1991) exploit the macroeconomics elements which leverage the US wheat price. Dahlgram and Blank (1992) study the American agriculture problem by the application of cointegration theory. Goleetti and Ahemd elaborate (1995) the Bangladesi rice price, based on the cointegration theory. Baulch (1997) further studies the American agriculture integration problem based on previous works. Ismet (1998) first introduces cointegration model to research Indonesian rice market. Yang and Leatham (1999) conflate the connotation of efficient market process(EMP) with idea of cointegration to reveal whether there is presence of long—run arbitrage in the US wheat market. Yang and Leatham (1999) point there is lack of solid evidence to support possibility of intertemporal speculation. Ghosh (2003) applies the maximum liklihood ration cointegration method to unveil the correlation between intra-state and outer-state price movement.

A number of articles relevant to the Chinese wheat price are published in domestic Chinese journals. With application of basic time series methods, Hu and Xue (2010) asserted that the 2008 financial crisis initiated from the US subprime market did not cause any substantial escalation in global grain price. Wang (2012) illustrates that under floating exchange rate system, agricultural products are less stable in face of erratic international market shocks.

By using the Granger causality test and the Impulse function test, Wang (2010) shows that mere impacts from fluctuation of crude oil price cannot move the long-run grian price away from equilibrium. Yang and Wang (2011) use the cointegration method to discern whether there is long-run correlation between inflation and wheat price. Results from the Granger test suggest the causal effect of inflation and wheat price is slightly insignificant, yet it is not negligible. Different from the aforementioned papers, in which authors use yearly data to study long-run correlation effect, Xu and Zhang (2012) analyze monthly data using the Hodrick-Prescott filter. Xu and Zhang (2012) stratify time series data of wheat price into five independent sections based on macroeconomic policies. They conclude government policies and natural disasters are pivotal in explaining volatile price in the grain market.

CHAPTER 3

UNIT ROOT TEST

3.1 Introduction of Unit Root:

Unit root data, namely I(1) for abbreviation, has drawn intens attention, given some idiosyncratic statistical and economic features. In the next paragraphes, I briefly discuss the basic concept of unit root, and its application in cointegration. Consider the following model:

$$y_t = m + \alpha y_{t-1} + \upsilon_t$$

$$y_t = (1+\alpha+\alpha^2+\alpha^3+\ldots)m + (\upsilon_t + \alpha\upsilon_{t-1} + \alpha^2\upsilon_{t-2} + \alpha^3\upsilon_{t-3} + \ldots)$$

$$E(y_t) = \left({1-\alpha^m}/{1-\alpha}\right)m$$

If $|\alpha|>1$, the whole series will diverge and never reach a steady state (Johnston and Dinardo, 2004). By knowing $\sigma_y^2 = E(y_t - \mu)^2$, if $|\alpha|>1$, there is no explicit expression of variance of y, which corresponds to the typical case of heteroskedastictiy; then the confidence interval we build is equipped with extremely low creditability, or even leads to an incorrect result.

If $|\alpha|<1$, the time series data is stable, and it eventually converges (Johnston and Dinardo, 2004).

if $|\alpha|=1$, then $\mathrm{Corr}(y_t, y_{t+h})$ manifests in form of $\sqrt{{t}/{(t+h)}}$, which violates basic rule of asymptotical uncorrelation (Johnston and Dinardo, 2004).

By inserting unstationary data into Ordinary Least Square equation, not only obtaining consistent estimators is unfeasible, but also the basic causal effect among variables is dubious (Wooldridge, 2004). In 1970s Granger and Newbold (1974) first processed a myriad pairs of I(1) data, with the benefits of modern computer technology. They studied 100 pairs of independent random walk time series data, such as average weight of cattle in Idaho and average income of janitors in Miami. Bewilderingly, 77 pairs of data demonstrate conspicuously high t-value, also Durbin-Wu test indicates no obvious sign of serial-correlation.

In 1987, Engle and Granger first explicitly introduce the idea of cointegration. The original work is beyond the scope of a succinct summary; the basic idea is to linearly rearrange two series of I(1) data y_t and x_t into $y_t - \beta x_t$, which is I(0)(Johnston, Dinardo). Johnston and Dinardo (2004) suggest $y_t = m + \lambda_1 y_{t-1} + \beta_0 x_t + \beta_1 x_{t-1} + \varepsilon_t$, by assuming $|\lambda_1| < 1$ and x_t is a random walk. y_t is a linear combination of I(1) and I(0), therefore y_t is I(1) series. Such as the equation: $y_t = m + \lambda_1 y_{t-1} + \beta_0 x_t + \beta_1 x_{t-1} + \varepsilon_t$

If we subtract from both sides y_{t-1}, and add and subtract $\beta_0 x_{t-1}$ from the right hand side (Johnston and Dicardo, 2004):

$$\Delta y_t = \beta_0 \Delta x_t - (1-\lambda_1)[y_{t-1} - a - \gamma x_{t-1}] + \varepsilon_t$$

$$a = {}^{m}\!/_{1-\lambda_1} \quad \text{and } \gamma = {}^{\beta_0+\beta_1}\!/_{1-\lambda_1}$$

By assuming, y_t and x_t are both I(1), so Δy_t and Δx_t are I(0). As for the equation in the bracket, if we entitle it as z_t and subtract from both side ${}^{m}\!/_{1-\lambda_1} + {}^{(\beta_0+\beta_1)x_t}\!/_{1-\lambda_1}$, then we have $z_t = \lambda_1 z_t + \upsilon_t$.

We already know $|\lambda_1| < 1$ and υ_t is white noise, thus we have obtained a new series of I(0) data by reparametrizing two strings of I(1) data.

3.2 Results from the Unit Root Test:

The tenor of this paper is to understand the underlying impacts from macroeconomic elements on long-term nominal wheat price. Previous papers are unanimously focused on the grain index, which contains all major crops, including wheat, corn, sorghum, and rice. In my paper, I concentrate on wheat price exclusively. The World Bank reports indicate Chinese wheat consumption relies highly on import from the US, Australia, and Canada. Since imported wheat accounts for majority of total consumption, the exchange rate becomes a pivotal elements in deciding long-run wheat price. The data come from database of Chinese National Bureau of Statistic and Chinese National Department of Agriculture and Fishery.

As we have discussed, before application of cointegration theory, stationarity of time series data needed to be ensured. Salient sign of either fast increases or decreases is troublesome. Since I only concerned with elasticity, only the log-transformed data is used. The succeeding graphs are time series data for CPI, nominal exchange rate, GDP, population, and nominal wheat price; log function is used for each individual variables.

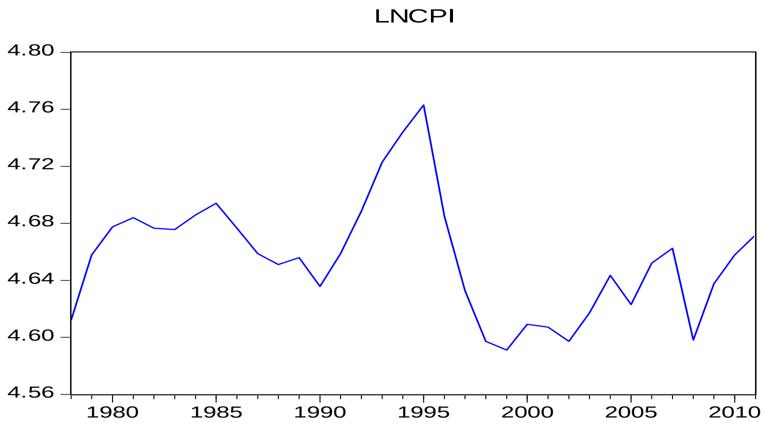

Figure 1

Time Series Data for ln(CPI)

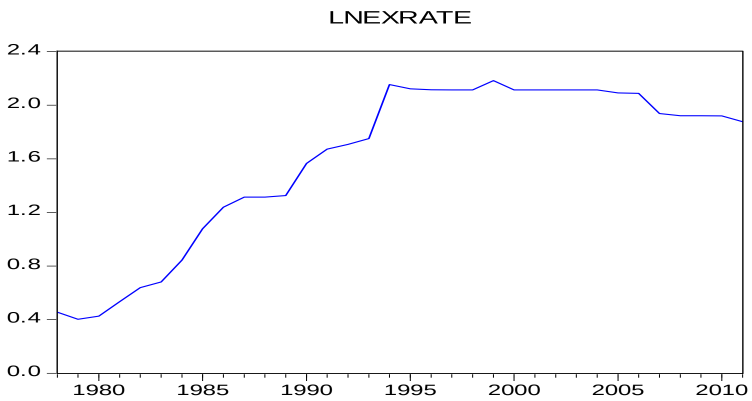

Figure 2

Time Series Data for ln(Exchange Rate)

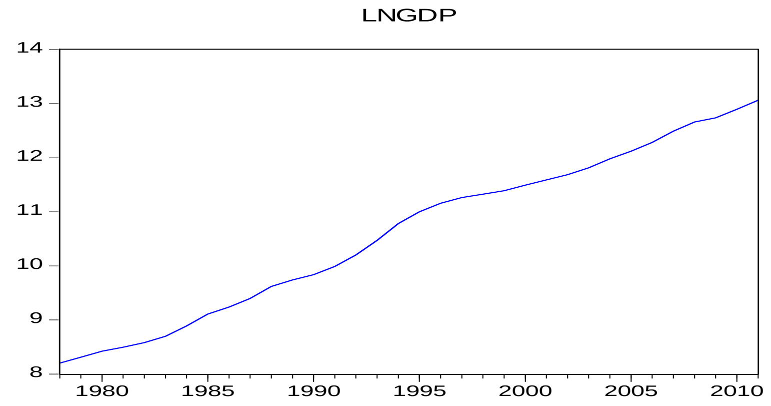

Figure 3

Time Series Data for ln(GDP)

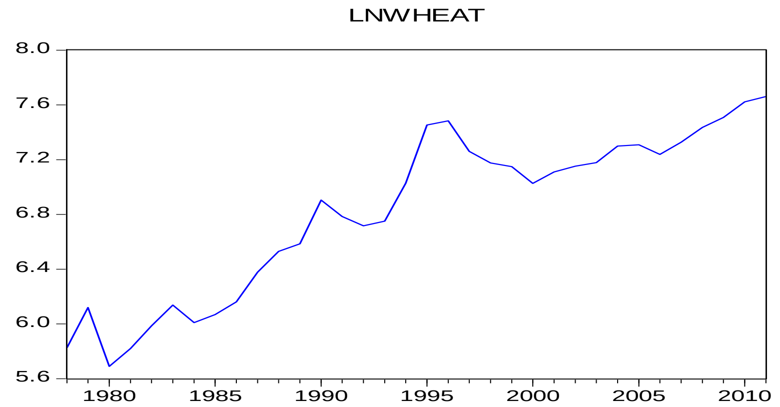

Figure 4

Time Series Data for ln(Wheat Price)

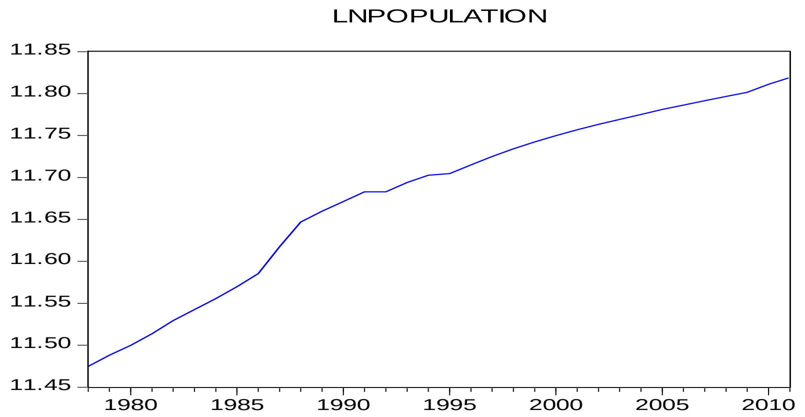

Figure 5

Time Series Data for ln(Population)

Except CPI, all variables indicate clear signs of tendency, so it is unstationary. Accurate calculation of stationarity needs to be conducted mathematically. There are many tests to detect stationarity, the most cited method is the Augmented Dicky-Fuller Test (ADF). According to Dickey-Fuller test, we should subtract y_t from both sides:

$$\Delta y_t = \delta + \rho y_{t-1} + \varepsilon_t$$

$$H_0: \rho<1$$

$$H_0: \rho=1$$

t- test is used to determine if stationarity is present.

Before using the cointegration model, we need to ensure all the time series data is in the form of I(1) (Wooldridge, 2004). Before we insert all the data into the cointegration model, unit root test is necessary to guarantee the plausibility of theory. First, we need to test if the level raw data is stationary.

Table 1

Null Hypothesis: Log wheat price has unit root

Lag Length: 0

		t-stat	Prob
Augmented Dicky—Fuller Test Stat		-1.059960	0.7196
Test critical value	1%	-3.646342	
	5%	-2.954021	
	10%	-2.615817	

Table 2

Null Hypothesis: Log CPI has unit root

Lag Length: 0

		t-stat	Prob
Augmented Dicky—Fuller Test Stat		-2.200577	0.2099
Test critical value	1%	-3.646342	
	5%	-2.954021	
	10%	-2.615817	

Table 3

Null Hypothesis: Log exchange rate has unit root

Lag Length: 0

		t-stat	Prob
Augmented Dicky—Fuller Test Stat		-2.324774	0.1705
Test critical value	1%	-3.646342	
	5%	-2.954021	
	10%	-2.615867	

Table 4

Null Hypothesis: Log population has unit root

Lag Length: 0

		t-stat	Prob
Augmented Dicky—Fuller Test Stat		0.136523	0.9635
Test critical value	1%	-3.646342	
	5%	-2.954021	
	10%	-2.615867	

Table 5

Null Hypothesis: Log GDP has unit root

Lag Length: 0

		t-stat	Prob
Augmented Dicky—Fuller Test Stat		-1.059960	0.7196
Test critical value	1%	-3.646342	
	5%	-2.954021	
	10%	-2.615867	

Results from table 1 to table 5 indicate all the variables do not comply with the pattern of I(0), whereas, degree of unstaionarity is unknown. I take first order difference to test if all variables are in the patterns of I(0), namely random walk.

Table 6

Null Hypothesis: Log wheat price has unit root

Lag Length: 1

		t-stat	Prob
Augmented Dicky—Fuller Test Stat		-5.789479	0.0000
Test critical value	1%	-3.646342	
	5%	-2.954021	
	10%	-2.615867	

Table 7

Null Hypothesis: Log CPI has unit root

Lag Length: 1

		t-stat	Prob
Augmented Dicky—Fuller Test Stat		-4.601784	0.0009
Test critical value	1%	-3.646342	
	5%	-2.954021	
	10%	-2.615867	

Table 8

Null Hypothesis: Log exchange rate has unit root

Lag Length: 1

		t-stat	Prob
Augmented Dicky—Fuller Test Stat		-4.306417	0.0019
Test critical value	1%	-3.646342	
	5%	-2.954021	
	10%	-2.615867	

Table 9

Null Hypothesis: Log population has unit root

Lag Length: 1

		t-stat	Prob
Augmented Dicky—Fuller Test Stat		-5.990294	0.0000
Test critical value	1%	-3.646342	
	5%	-2.954021	
	10%	-2.615867	

Table 10

Null Hypothesis: Log GDP has unit root

Lag Length: 0

		t-stat	Prob
Augmented Dicky—Fuller Test Stat		-3.761896	0.00932
Test critical value	1%	-3.646342	
	5%	-2.954021	

Results from table 5 to table 10 suggest, based on Augmented Dicky-Fuller test, all variables are in the form of I(0). Therefore, we conclude all the variables satisfy the requirement for cointegation test.

CHAPTER 4

CONSTURCTION OF VAR MODEL

Cointegration theory is orchestrated on the basis of VAR model. VAR model is a system of autoregressive equations. Theoretically, regressands can be taken in the form of infinite lags of other cointegrated variables. As the central limit theory plays key role in the study of heteroskedasticity, without innovation of VAR, cointegration theory is no different than a regular high-degree AMAR model. Traditional MA and AMAR model is confined by the number of autogressive variables. In other words, MA and AMAR models exclude the possibility to simultaneously disclose the autogression among various variables. Although, in 1960s and 1970s, some statisticians and economists have already shed light on this problem, complete solution is developed by Sims (1980) .

Johnston and Dinardo (2004) offer a laconic summary of the essential ideas of VAR model.

$$y_{1t}=m_1+a_{11}y_{11,t-1}+a_{12}y_{2,t-1}+\varepsilon_{1t}$$

$$y_{1t}=m_2+a_{11}y_{21,t-1}+a_{22}y_{2,t-1}+\varepsilon_{2t}$$

In brief, we can reinterpret the equation system in the matrix form, with only two independent variables and one lag.

$$\mathbf{y_t}=\mathbf{m}+\mathbf{A}\mathbf{y_{t-1}}+\boldsymbol{\varepsilon}_\mathbf{t}$$

$$\boldsymbol{\Lambda}=\begin{pmatrix}\lambda_1 & \mathbf{0}\\ \mathbf{0} & \lambda_2\end{pmatrix}\quad \mathbf{C}=\begin{pmatrix}c_{11} & c_{12}\\ c_{21} & c_{22}\end{pmatrix}$$

If we subtract $\mathbf{y_{t-1}}$ from both sides**,** then the above equation becomes:

$$\boldsymbol{\Delta}\mathbf{y_t}=\mathbf{m}-(\mathbf{I}-\mathbf{A})\mathbf{y_{t-1}}+\boldsymbol{\varepsilon}_\mathbf{t}$$

$$\boldsymbol{\Pi}=\mathbf{I}-\mathbf{A}$$

Based on the understanding of the basic form of a VAR system, we could solve the equation system with knowledge of basic linear matrix.

Case1: $|\lambda_1|<1$ and $|\lambda_2|<1$, both series are stationary I(0). Ideal static equilibrium is attainable.

Case2: $|\lambda_1|$=1 and $|\lambda_2|$<1. By taking first difference of series one and reparamaterizing the original equation, cointegration between two variables is theoretically possible.

Case2: $|\lambda_1|$=1 and $|\lambda_2|$=1, which means the two series of data are linearly independent. In the

In the long-run, a rapid of one economic variable will not precipitate the rapid increase of another series. In Johansen's original paper (1990), a more comprehensive illustration could be found. Any variable can be written as any finite lags of linear combination of other variables. As the subsequent equation shows:

$$\mathbf{\Delta y_t = m + B_1\,\Delta y_{t-1} + \cdots + B_{p-1}\,\Delta y_{t-p+1} - \Pi y_{t-1} + \varepsilon_t}$$

$$\mathbf{\Pi = I - A_1 - \ldots - A_p}$$

$\mathbf{\Pi}$ is composed of multiply of two p*k matrix, which can be presented as $\Pi = \boldsymbol{\alpha\beta'}$**.**

Case 1: Rank(Π**)=**k, each root has modulus less than one, Π will be full rank(Johansen).

Case 2: Rank(Π**)=**r<k, there are r roots smaller than one, which means there are r cointegraiton variables.

Case 3: Rank(Π**)=**0, which suggests that VAR should be specified solely in terms of first difference of variables.

In case 1, all series of data are in I(0) form, OLS is usually used for consistent estimators, application of the cointegration theory could be redundant. Case 2 is most commonly seen, which suggests there are r variables ready for use of the cointegartion theory. The last case refers to all variables being I(1), in which case only the first difference can give meaningful results. We have already done the unit root test before, and all variables in our experiment exhibit the I(1) form. Therefore, our data complies with precondition for cointegration.

Lutkepohl and Helmut (1991) declare all modulus of roots need to be smaller than one in order to have a stable VAR system. The following graph is the result of the modulus test, with package of variables, including population, exchange rate, GDP, CPI, and wheat price.

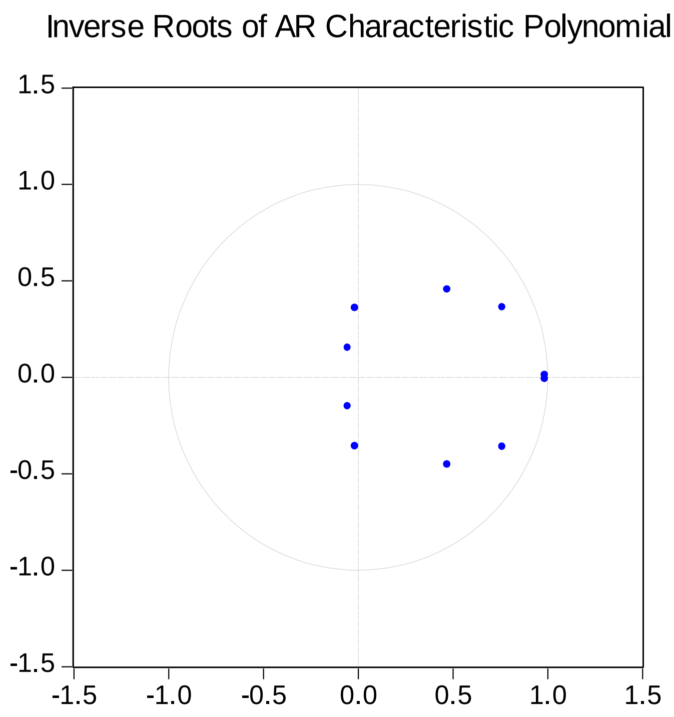

Figure 6
Modulus Root Test for VAR Model

The above graph shows all modulus of roots are less than one (the two points close to the circle are both 0.995167), indicating that the VAR model we build is stable.

CHAPTER 5

OPTIMAL LAG ORDER

VAR model allows cointegrated variables to take any order of lags in the system of equations, so it is necessary to determine which order results in optimal efficiency. James Hamilton (1994) provides an explanation of how to determine optimal lag length. He proposes a hypothesis about the maximum lag length of p_1, then he tests each order $p_0 < p_1$ until he can find the p_0 , which he can reject the null hypothesis , by application of the maximized log likelihood test. Hamilton (1994) shows the maximized log likelihood is l_0=constant+$\frac{n}{2}\ln\left|\hat{\Omega}_0{}^{-1}\right|$, in the case of lag length of p_0. Analogously, when lag length is a presumed value p_1, l_1=constant+$\frac{n}{2}\ln\left|\hat{\Omega}_1{}^{-1}\right|$.

$\hat{\Omega}$ is the estimated variance-covariance matrix. We could test whether LR= -2(l_0-l_1)=n[ln$\left|\hat{\Omega}_0{}^{-1}\right|$- ln$\left|\hat{\Omega}_1{}^{-1}\right|$]$\approx X^2$(q) ,to determine if we reject the null hypothesis or not (Hamilton, 1994).

Table 11

Results For Optimal Lags Test

Lag	LogL	LR	FPE	AIC	SC	HQ
0	108.0872	NA	1.33e-09	-6.247708	-6.020965	-6.171416
1	332.7126	367.5689*	7.57e-15*	-18.34622*	-16.98576*	-17.88847*

As we can see in this table, with lag length one, all the statistics show at least one asterisks, which implies the optimal choice.

CHAPTER 6

COINTEGRATION

6.1 Johansen Cointegration Test:

The Johansen test is entitled after the Danish econometrician Johansen. Johansen makes an innovation based on Engle's original design. The following two tables represent significance test by the Johansen cointegraton test.

Table 12

Unrestricted Cointegration Rank Test(Trace)

Hypothesized NO.of CE(s)	Eigenvalue	Trace Statistic	0.05 CriticalValue	Pro**
None	0.902738	234.12340	69.81889	0.0000
At Most 1*	0.866834	164.2127	47.85613	0.0000
At Most 2*	0.825627	103.7279	29.79707	0.0000
At Most3*	0.609044	51.33123	15.49471	0.0000
At Most4*	0.537858	23.15646	3.841466	0.0000

Trace test indicates 5 cointegration eqn(s) at 0.05 level

*denotes rejection of the hypothesis at 0.05 level

Table 13

Unrestricted Cointegration Rank Test(Maximum Eigenvalue)

Hypothesized NO.of CE(s)	Eigenvalue	Max—Eigen Statistic	0.05 CriticalValue	Pro**
None	0.902738	69.91032	69.81889	0.0000
At Most 1*	0.866834	60.48481	47.85613	0.0000
At Most 2*	0.825627	52.39669	29.79707	0.0000
At Most3*	0.609044	28.17477	15.49471	0.0002
At Most4*	0.537858	23.15646	3.841466	0.0000

Trace test indicates 5 cointegration eqn(s) at 0.05 level

*denotes rejection of the hypothesis at 0.05 level

The preceding tables give consistent results which affirm all four explanatory variables are significant in the cointegration test. Algorithm underlying the two tests are distince, which would create a problem if they were to produce contradictory results. Luckily, in this case, results of these two tests impart are consistent.

Johenston (1988) designed the cointegration test with application of the maximum eigenvalue test. Osterwald (1992) explained the cointegration theory from a different perspective, by using the definition of matrix rank.

Both the trace and maximum eigenvalue tests are derivations from the LR ratio, yet the methodologies are substantially different. If we define: $\Delta Y_{t-1}^{t-p+1} = Y_{t-1}^{t-p+1} + Y_{t-2}^{t-p}$, through OLS regression of Δy_t and y_t on ΔY_{t-1}^{t-p+1}respectively, we obtain residuals R_{0t} and R_{1t} (Lutkepohl,2002). Equipped with concept of $S_{ij} = T^{-1} \sum_{t=1}^{T} R_{0t} R_{1t}{}'$,we could retrieve the eigenvalue by solving for the determinant of

[λS_{11}-$S_{10}S_{00}{}^{-1}S_{00}$]=0.(Johenson, 1991).

Due to a heterogeneous null hypothesis, the likelihood ratio test of two methodologies slightly differs. For the trace test, $LR_{trace}^{0}(r_0)$=-$T\sum_{j=r_0+1}^{n} \log(1-\lambda_j)$. For the maximum eigenvalue test: $LR_{max}^{0}(r_0)$=-$T\log(1-\lambda_{r_0+1})$ (Johenson,1995). Given the disparity between the two LR test, the trace test and maximum likelihood test asymptotically converge to different distribution. $\mathrm{LR}^0_{\mathrm{trace}} \xrightarrow{d}$ trace(D) and $\mathrm{LR}^0_{\max} \xrightarrow{d}$ $\lambda_{\max}(D)$, $D=(\int_0^1 \mathrm{F}\,\mathrm{dN}')'(\int_0^1 \mathrm{F}\,\mathrm{F}'\mathrm{ds})^{-1}(\int_0^1 \mathrm{F}\,\mathrm{dN}')$;F(s) is an (n-r_0) dimension stochastic process and N(s) is the Ornstein-Uhlenbeck process defined by N(s)=B(s) + $\mathrm{ab}' \int_0^1 \mathrm{N(u)du}$, B(s) is a standard Brownian motion. (Lutkephol, 2000).

6.2 Cointegration Results:

The following table shows coefficients of the four independent variables, from cointegrated regression:

Table 14

Cointegration Coefficient(Standard Error in Parenthesis)

LnWHEAT	lnCPI	lnGDP	lnEXRATE	lnPOPULATION
1.000000	-7.238706	0.150410	0.044019	8.695492
	(0.62169)	(0.04009)	(0.06461)	(0.85299)

Each individual variable is expressed as an elasticity. The table above refers to ascension of CPI by 7.23%, correspondingly wheat price will decrease by one percent. This result seems to be contradictory to what we normally conceive; with ballooning consumption index, the nominal wheat price decreases. Wheat , though is one of the most pivotal part for Chinese grain consumption, rice and maize may act as substitute commodity, when wheat consumption is under pressure of price inflation. Zhi xin asserts global wheat price has gone through a process of drastic increase from 2007 until 2009, while Chinese wheat price only slightly elevates by less than 4%, partially attributed to massive import of maize as substitute(Zhi, 2011). Rice, as major substitue commodity for wheat, accounts for more than 55% of whole of entire grain consumption. With enhancing bio-technology and transgenetic techniques, rice become more prolific and productivity almost tripled (Niu and Naveen, 2013).

Another mitigating method for increase in domestic wheat price is import. With higher level of CPI, the domestic wheat price reasonably elevates as other normal commodities. Notwithstanding, as wheat is the major source of grains for daily consumption, Chinese wheat consumers may switch to cheaper wheat from foreign market, under the challenge of inflation. Therefore, even in the relative long-term, a rising consumption index would be an ambiguous indicator of a clear trend of increasing wheat prices.

GDP, manifests in positive cointegrated relationship with the wheat price. As nominal GDP increases by 0.15%, the wheat price increases by one percent. It is plausible to perceive a conspicuous positive correlation between GDP and the wheat price, since wheat feeds almost half a billion Chinese in Northern China, and few provinces in the South (Zheng, 2008). Since the inception of economics reform, crop productivity and diet habit has morphed through a process of conversion. In the 1980s and early 1990s, the Chinese GINI index was higher than global average. Regular Chinese families were frugal with respect to spending income on non-sustainable products, most disposable income is consumed for food. As the World bank report (2009) suggests , once per-capita GDP reaches $1,350 annually, residents would take other protein rich food as substitutes for wheat; leading to an eventual reduction of demand in wheat. (Zhang & Wang, 2011). Today, per-capita GDP in China is around $1,200. If the Chinese economy remains on the rapid pace of growth, wheat demand will be weaker than before.

The nominal exchange rate moves positively in tandem with the price of wheat. Chinese nominal exchange rate is the price of the US dollar measured as units of the Chinese RMB. An increase in the nominal exchange rate indicates Chinese RMB is depreciating. My results indicate that as the Chinese RMB devalues by 0.045%, domestic wheat price increases by one percent.

According to the magnitude of coefficients, the impact of the exchange rate on the wheat price is salient. For instance, in the year 2008, the nominal exchange rate of the Chinese RMB was 6,83, and wheat price was $248.169 per ton; a one percent increase in the nominal exchange rate, results in the wheat price increasing by almost $60 . Empirically, the wheat price does not fluctuate significantly as the theory suggests, neither is the oscillation of short-term wheat price instantaneously mirrored by a volatile exchange rate. However, the trend is clear and unambiguous.

A constant drizzle and harsh frost in the spring of 2013, drenched the newly sprouted wheat back to germination and deferred the harvest time (Niu and Naveen, 2013). Major wheat cultivation areas, such as Shandong and Henan were afflicted by a drastic decline of wheat productivity (Meyer, 2013). Based on reports, at least 20 million tons of wheat had evaporated, due to atrocious weather (Phoebe, 2013).

Usually, under duress from a nature disaster, the Chinese government usually allocates reserved grains to affected areas. This year, with constantly appreciating Chinese currency, the central government was not hesitant to import wheat from Australia and Canada. In spring of 2013, three million tons of wheat had been purchased from Australia; more orders were expected in the following months, as the deteriorating frost persisted (Niu and Naveen, 2013). China surpassed Egypt to become the largest wheat importer, earlier in 2013. Reports indicate, if the Chinese currency keeps its strong momentum of appreciation, another 5 million tons of wheat are about to be purchased. (Niu and Naveen, 2013).

Population exhibits a positive sign in our cointegration result. The above table suggests that an 8.69 percent increase in population will result in one percent inflation in wheat prices. The t-value is almost 11, which shows tangible significance. Population, by no means, would go through neither a rapid rise nor rapid decrease in a short period of time. Not to mention that the Chinese government imposes an ironclad policy preventing a large population growth rate. However, the cointegration test offers us a clear picture that with an expanding population, the pressure on wheat price would be noticeable.

CHAPTER 7

GRANGER CAUSALITY TEST

7.1 Methodology:

As foregoing sections imply, time series data in form of I(1) are displayed in trajectory of divergence. Granger and Newbold (1974) first showed that running OLS of I(1) data often cause a deceptive correlation between two series of irrelevant variables such as rate of prostate cancer and consumption on lottery ticket.

With limited understanding of exogeneity, it is impossible to present a satisfactory elaboration on Granger causality. Indeed the two ideas are closely interwoven. Since the discovery of Granger causality, time series econometricans have a more profound understanding of previously bewildering questions, including exogeneity or even autorgression. Inspired by Grnager's causality theory, Robert Engle published a series of papers pertaining to exogeneity in the early 1980s.

Granger (1969) thoroughly solved the problem of one direction causality. He also provides a comprehensive solution to the more sophisticated case of "feedback" causality. In this paper, Granger (1969) initiates frequency of data collection is also critical to detect causality. Inefficient behavior of data collection may miss pivotal information and leads to conclusion of instantaneous causality.

In the most abstract case of spectral methods, X_t and Y_t are both stationary time series, then X_t is expressed in form of X_t=$\int_{-\pi}^{\pi} e^{it\omega} dZ_x(\omega)$; $Z_x(\omega)$ is a complex random process E[$dZ_x(\omega)\overline{dZ_x(\lambda)}$]= $dF_x(\omega)$,if $\omega = \lambda$, otherwise E[$dZ_x(\omega)\overline{dZ_x(\lambda)}$]=0(Granger, 1969). $dF_x(\omega)$ can be written as $dF_x(\omega)$= $f_x(\omega)d\omega$. $Cr(\omega)$ is the cross spectrum between X_t and Y_t, which is composed as E[$dZ_x(\omega)$ $\overline{dZ_x(\omega)}$]= $Cr(\omega)d\omega$, if $\lambda \neq \omega$(Granger ,1969).

Then the covariance between X_t and Y_t is composed as μ_t^{xy} =E[$X_t\overline{Y_{t-\tau}}$]= $\int_{-\pi}^{\pi} e^{i\tau\omega} Cr(\omega) d\omega$ (Granger,1969). $\bar{X}$ is the time series data only including lagged values of x, $\bar{\bar{X}}$contains information of both previous lags and current data; $\bar{X}$ ={X_{t-i}| i=1,2,3… ∞}, $\bar{\bar{X}}$={X_{t-i}| i=0,1,2,3… ∞}(Granger,1969).

The more subtle connotation of feedback and instantaneous causality can be decomposed into the basic spectral models. By grasping the fundamental concepts, Granger gives a qualitative definition of degree of causality in the spectral case:*C(ω)*= $|Cr(\omega)|^2 \big/ f_y(\omega) f_x(\omega)$. Additionally, Granger (1969) emphasize frequency of data collection is often negligible, yet critical to determine causality. Granger (1969) illustrates Ø(ω)=$tan^{-1}\frac{imanginary\ part\ of\ Cr(\omega)}{real\ part\ of\ Cr(\omega)}$, which detect phase difference of varied frequency. With a solid grip of the rudimentary spectral method, we can easily fathom the mechanism of *feedback causality*, which can be decomposed into a summation of two spectral series.

Rhetorically, *feedback* indicates a pattern of interaction, in time series topic this implies bilateral causality between two series of data X_t and Y_t. The symbolic expression is $X_t \Rightarrow Y_t$, meanwhile, $Y_t \Rightarrow X_t$. The gist of Granger causality is to test if there is salient reduction in the error term σ, by plugging in a series of lagged data of a new variable(Colin and Pravin, 2005). For instance, with y_t =β_0+$\beta_1 y_1$+$\beta_2 y_2$+…+$\beta_k y_k$+σ_y, once a series of lagged x_t is inserted into the original equation, then y_t =β_0+$\beta_1 x_1$+$\beta_2 x_2$+…+$\beta_k x_k$+$\beta_1' y_1$+$\beta_2' y_2$+…+$\beta_k' y_k$ +σ_x. If σ_x is ostensibly smaller than σ_y, we assert there is an intrinsic causality from series X_t to series Y_t.

Granger (1969) uses U_t to represent information embodied with the whole package of explanatory variables and independent variables; U_t-Y_t, stands for information which purged with the impact from Y_t. Granger (1969) asserts that for circumstance of $\sigma^2(X|U)$ < $\sigma^2(X|\overline{U-Y})$, $Y_t \Rightarrow X_t$ (Granger,1969). A typical *feedback* case complies with the condition of $\sigma^2(X|U)$ < $\sigma^2(X|\overline{U-Y})$ and $\sigma^2(Y|U)$ < $\sigma^2(X|\overline{U-X})$, then we could claim $X_t \Leftrightarrow Y_t$.

7.2 Result:

After a quick review of the methodology underlying the Granger causality test, I will examine the causality between the four macroeconomic variables and the yearly wheat nominal price.

Table 15

Var Granger Causality/ Block Exogeneity Wald Test

Dependent Variable:ln(wheat price)			
Excluded	Chi—sqr	df	Prob
lnCPI	21.43558	2	0.00000
lnGDP	6.047021	2	0.0486
lnEXRATE	3.67164	2	0.03883
lnpopulation	14.75462	2	0.0006
All	68.21360	8	0.00000

As the table shows, the macro elements share a strong causal relationship with the wheat price. Increasing CPI and population inevitably induce wheat prices to ramp up. GDP, which is a key indicator of the general economic environment, only suggests a slight causality with the wheat price. We would reject the null hypothesis that GDP has no causal relation to the wheat price, at the significance level of 5%. A rapid growth of the economy, does not change diet habit over night. Only when per capita GDP attains a certain level, would people gradually attracted to higher protein food.

The exchange rate, suggests a clear causality with the wheat price. A shock in foreign exchange market could ripple to the grain market. An appreciating Chinese RMB will induce domestic buyer to participate in the cheap foreign wheat market.

For comparison, in table 16, we set lnGDP as a dependant variable, and test causality of wheat price, population, CPI, and exchange rate to GDP.

Table 16

Var Granger Causality/ Block Exogeneity Wald Test

Dependent Variable:lnGDP			
Excluded	Chi^2	df	Prob
lnwheat	0.413328	2	0.8133
lnCPI	5.861931	2	0.0533
lnEXRATE	0.569092	2	0.7524
lnpopulation	4.368357	2	0.1125
All	11.98262	8	0.1520

This table indicates that as we set the GDP as regressor, only the CPI manifests slim causality to GDP. The wheat price and the exchange rate are causally irrelevant to increases in GDP, while even population shows no obvious causality. Notwithstanding, application of OLS may still induce a spurious correlation, given a significant level of t-value.

CHAPTER 8

IMPULSE RESPONSE FUNCTION

Since the invention of a VAR model, time—series analysis for macroeconomics data process has reached a novel era. In 1980s, Sims (1980) devalued the empirical usefulness of VAR model, due to its unrealistic constraint on the equation system. As complementary for the VAR model, the impulse response function makes its first appearance in the late 1980s, after a decade of consistent enhancements, the final step being undertaken by Koop in 1996.(Gao, 2009).

For the equation system of VAR model with lag one is:

$$y_{1t}=m_1+a_{11}y_{11,t-1}+\ a_{12}y_{12,t-1}+\ldots+a_{1k}y_{1k,t-1}+\varepsilon_{1t}$$

$$y_{2t}=m_2+a_{21}y_{21,t-1}+\ a_{22}y_{22,t-1}+\cdots+a_{2k}y_{2k,t-1}+\varepsilon_{2t}$$

$$\vdots$$

$$y_{kt}=m_1+a_{11}y_{k1,t-1}+\ a_{k2}y_{2,t-1}+\cdots+a_{1k}y_{1k,t-1}+\varepsilon_{kt}$$

If there is an exogenous shock for ε_{1t} at period 0, only y_{1t} changes in the current period. However, the ripple effect of an exogenous shock will cause a fluctuation of other variables through the autogressive equation system. The exogenous impact for certain variables may gradually spill over to other variables, eventually imposing a long-run impact in the entire system (Johnson and Dinardo, 2004).

The table 17 shows the long-run impulse response of GDP, CPI, population, and the exchange rate, once a shock affects them.

Table 17

Reponse of lnwheat to shock from lnGDP, lnCPI, lnpopulation,lnexrate

period	lnGDP	lnCPI	Lnexrate	lnpopulation
1	0.0000	0.0000	0.0000	0.0000
2	0.0435	0.0122	0.0369	0.0243
3	0.0621	0.0128	0.0297	0.0301
4	0.0578	0.0241	0.0241	0.0093
5	0.0384	0.0212	0.0335	-0.0093
6	0.0157	0.0103	0.0482	-0.0226
7	-0.0003	0.0014	0.0567	-0.0282
8	-0.0073	0.0015	0.0537	-0.0258
9	-0.0075	0.0006	0.0411	-0.0187
10	-0.0039	0.0052	0.0246	-0.0103

The response in the wheat price is zero in the first period. When there is a shock in the exchange rate, it will not be instantaneously reflected in the wheat price; but the effect will gradually dissipate from the foreign currency market to wheat market. As we can see from the table, when there is a positive shock on the exchange rate depreciating the Chinese RMB, then long-run rise in wheat prices is foreseen, yet the magnitude dimishes over time.

Figure 7 tells the same story table 17. However, the diagram usually imparts information more acceptable through visual depiction.

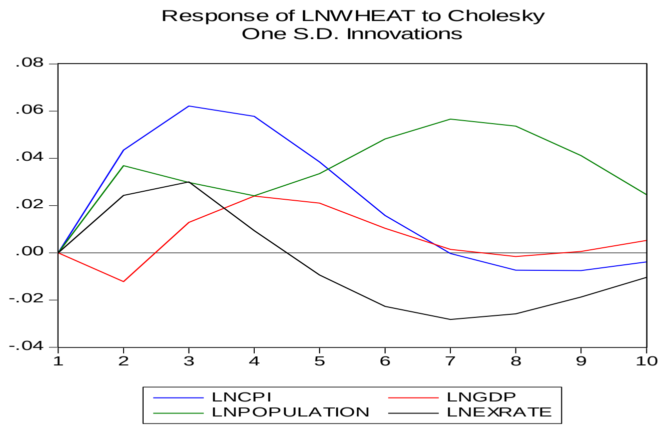

Figure 7

Diagram of Impulsive Response Function on Wheat Price

CHAPTER 9

Conclusion:

Since the inception of Chinese economic reform, and under the increasing pace of globalization, Mao's utopian equalitarian system crumbled. The traditional rationing system turns into a fiasco, due to inefficient information gathering and a lack of individual incentives. However, the traditional model of supply and demand is unable to unveil price shocks in the wheat market. At least, the conventional study of demand and supply in close market is weak, given the massive volume of wheat imported from the United States and Canada.

In this paper, I use GDP, CPI, population, and the exchange rate as explanatory variables to reveal the effects of major macroeconomic forces on the nominal Chinese wheat price. Though the Chinese government vehemently defends its wheat supply as self-sustainable, the World Bank report purpors a high-degree of reliance on imports (Food Watch, 2011). The exchange rate, which is a pivotal factor in determing the price, remains vague, given political emphasis on domestic production.

In chapter three, I present a brief introduction of the unit root, followed by empirical results from the unit root test. In chapter four, I explains how to build a VAR model for the purpose of conducting the cointegration test. Theoretically, a VAR model allows cointegrated variables to take any finite order of lags. Therefore in chapter five, the optimal lag order is determined. Generally, most estimators from the cointegration test agree with my original hypothesis. Increasing price level and population size increase the wheat price to a higher level. Essentially, a conspicuous correlation between appreciating Chinese RMB and increase in wheat imports is discerned. In case of a spurious regression, the Granger causality test is conducted. Finally, I apply the impulse response test to delineate a dynamic procedure, under the effects of exogenous shocks.

Although debates on the linear constraint of VAR model still persists. Given the current computational capabilities of most modern computers, the VAR model is still the most commonly used method for processing small size multivariate time series data (Granger and Leone, 2002). Cointegration, which is operated based on the VAR model, is widely cited in the fields of financial economics and macroeconomics.

References

Agricultural Commodity Price Study During the Eleventh Five Year Growth Plan—With Application of Cointegration Theory and VAR Model. *Collected Essay on Finance and Economics. Volume 158, Issue 3.*

Agriculture Price Instability: A Survey of Competing Explanations and Remedies. (2012). *Journal of Economic Surveys. Volume 26, Issue 1, pp.129–156.*

Artstein, Z. (1983) Irregular Cobweb Dynamics. *Economics Letters.Volume 11, p15–17.*

Baulch, B. (1997) Transfer Costs, Spatial Arbitrage, and Testing for Food Market Integration. *American Journal of Agricultural Economics. Volume 79, pp. 477–487.*

Buchanan, N.S. (1939) A reconsideration of the cobweb theorem. *The Journal of Political Economy. Volume 47, pp.67–8.*

Brock, W.A. and Hommes, C.H. (1997) A Rational Route to Randomness. *Econometrica. Volume 65, pp.1059–1096.*

Chambers, R G , and Just. R. E. (1986)A Cntique of Exchange Rate Treatment and Agricultural Trade Models Reply. *American Journal of Agricultural Economics. Volume 68, pp.994- 997.*

Dahlgram, R.A. & Blank, S.C. (1992). Evaluating the Integration of Continuous Discontinuous Markets. *American Journal of Agricultural Economics.Volume 74, pp.469–479.*

Dornbusch, R. (1976). Expectations and Exchange Rate Dynaffilcs. *Journal of PolitIcal Economy. Volume 84, pp.1161-1176.*

Engle. R. F and Granger. C.W. Cointegration, Error Correction: Representation, Estimation, and Testing. *Econometrica. Volume 55, pp.251—276.*

Ezekiel, M. (1938) The cobweb theorem. *The Quarterly Journal of Economics. Volume 52, pp.255–280.*

Food Price Watch. (July, 2011). Poverty Reduction&Equity. The World Bank.

Food Price Watch. (July, 2011). Poverty Reduction&Equity. The World Bank

Gao, T. (2009). *Econometric Analysis and Modeling—with Eview application and Empirical Case study.*

Ghosh, M. (2003). Spatial Integration of Wheat Markets in India: Evidence from Cointegration Tests. *Oxford Development Studies. Volume 31, pp.159—171.*

Goletti, F. and Ahmed, R. and Fraid, N. (1995) Structural Determinants of Market Integration: the Case of Rice Markets in Bangladesh. *The Developing Economies Volume 33, pp. 185– 202.*

Granger. C. W. and Newbold, P. Spurious Regression in Econometrics. *Journal of Econometrics. Volume 2, pp.111—120.*

Hooton, J. and Akerman, C. and Akerman, G. (1957). The Cobweb Theorem: a Reconsideration. *The Quarterly Journal of Economics. Volume 71. pp.263-271.*

Hu. B. and Xu, F.and Gao, X. (2010). Study for Underlying Elements for International Agricultural Price Fluctuation—Based on Basic Time Series Model. *Journal of Huazhong University of Science and Technology. Volume 3, pp. 137-153*

Ismet, M., Barkley, A.P. & Llewelyn, R.V. (1998) Government Intervention and Market Integration in Indonesian rice Markets. *Agricultural Economics. Volume 19, pp. 283–295.*

Jensen, R.V. and Urban, R. (1984) Chaotic price behavior in a non-linear cobweb model. *Economics Letters. Volume 15, pp.235–240.*

Johnson, J and Dinardo, N (2004) *Econometric Methods* (4th ed.) The McGraw-Hill Companies, Inc, 2004. Print.

Jian Yang and David J. Leatham. (1998).Market Efficiency of US Grain Markets: Application of Cointegration Test. *Agribusiness. Volume 14, pp.107-112.*

Lutkepohl, K. (2002). Maximum Eigenvalue Versus Trace Tests for Integration Rank of a VAR Process. *Discussion Papers, Interdisciplinary Research Project 373: Quantification and Simulation of Economic Processes, No. 2000,83*

Mark, D and David, T. (1991). Macroeconmic Determinants of Relative Wheat Prices: Integrating the Short Run and Long Run. *The Journal of Agricultural Economics Research. Volume 44, Issue 2.*

Muth, J. (1961). Rational Expectations and the Theory of Price Movements. *Econometrica. Volume 29, pp.315–335.*

Nationalmaster Agriculture Database

Norbu, J. (March, 2011). Dipping a Donkey-Ear in Butter Tea. *Shadow Tibet*.

Orden, D. (1986) . A Critique of Exchange Rate Treatment In Agncultural Trade Models Comment. *American Journal ofAgricultural Economics. Volume 68, pp.990-993.*

Poverty Reduction and Equity Group Poverty Reduction And Economic Management(PREM). (November, 2012). *Network The World Bank. Volume 3, Issue 12.*

Poverty Reduction and Equity Group Poverty Reduction And Economic Management(PREM). (November, 2011). *Network The World Bank. Volume 2, Issue 11.*

Sims.C.A. (1980). Macroeconomics and Reality. *Econometrica. Volume 48. Issue 1 pp.1-48.*

Viveros, Z. (August 30, 2012). Severe Drought Drive Wheat Price Higher, Threatening the Poor. *The World Bank-Working For a World Free of Poverty*. Retrived from

Kuijs, P. (2011). China's Food Price—Why Have They Trended Up and What Lied Ahead. *Blogs.Worldbank.Org.*

Wang, N. (2012). Agricultural Products Price Fluctuation Under Floating Rate. *Agricultural Economics. Volume 5, Issue 3. pp.23-41.*

Wooldridge, J. (2004). *Introductory Econometrics.* South-Western Cengage Learning, 2004. Print.

Xue, Y. and Zhang, S. (2012). Dynamic Analysis of Cyclic Features in Chinese Wheat Price. *Productivity Research.*

Yang, J and Leatham, J. (1999). Price Discovery in Wheat Future Markets. *Journal of Agricultural and Applied Economics. Volume 31, Issue 2, pp.359-370.*

Yang Z. and Wang, Y. (2011). Empirical Research on Causal Correlation Between Agricultural Products Price and National Inflation. *Statistic and Strategy. Volume 324, Issue 34.*

Zhang, T and Wang, M. (2011). Rudimentary Study of Chinese and Global Wheat Consumption. *The Journal of Chinese Rural Report. Volume 43. Issue 5. pp. 231-244.*